Agriculture, Forestry and Fisheries
2021; 10(2): 85-92
http://www.sciencepublishinggroup.com/j/aff
doi: 10.11648/j.aff.20211002.17
ISSN:2328-563X (Print); ISSN:2328-5648 (Online)

Maize Growth (*Zea mays l.*) Modeling Using the Artificial Neural Networks Method at Daloa (Côte d'Ivoire)

Kouame N'Guessan[1, *], Assidjo Nogbou Emmanuel[2]

[1]Agricultural Production Improvement Laboratory, University Jean Lorougnon Guede, Agroforestry Training and Research Unit, Daloa, Côte d'Ivoire

[2]Laboratory of Industrial Synthesis and Environment Processes, National Polytechnic Institute Felix Houphouët-Boigny, Yamoussoukro, Côte d'Ivoire

Email address:

maximekouamelma@yahoo.fr (K. N'Guessan)

[*]Corresponding author

To cite this article:

Kouame N'Guessan, Assidjo Nogbou Emmanuel. Maize Growth (*Zea mays l.*) Modeling Using the Artificial Neural Networks Method at Daloa (Côte d'Ivoire). *Agriculture, Forestry and Fisheries*. Vol. 10, No. 2, 2021, pp. 85-92. doi: 10.11648/j.aff.20211002.17

Received: February 23, 2021; **Accepted**: March 8, 2021; **Published**: March 26, 2021

Abstract: The growth of maize is a complex phenomenon which involves certain parameters including the number of leaves, the length of the leaves, the width of the leaves, the height and the circumference of the plant. A study of these growth parameters was carried out in the region of Daloa (Côte d'Ivoire). These measurements could show a complexity of the growth of maize. To this end, mathematical models have been developed to predict this growth from artificial neural networks for the number of leaves, the length of the leaves, the width of the leaves, the height of the plant and the circumference of the trunk of the maize plant. The coefficients of determination between the experimental measurements and the measurements predicted by artificial neural networks are respectively 0.9914; 0.9965; 0.9872; 0.9995 and 0.9976 for plant height; the number of leaves; the circumference of the plant; leaf length and leaf width. Satisfactory results have been obtained insofar as all the coefficients of determination are greater than 0.98. These coefficients close to 1 show a good interpolation between the experimental values and those predicted by the model. Because of this, we can say that the values predicted by the artificial neural network are reliable enough to predict the growth of maize.

Keywords: Maize, Growth Parameter, Modeling, Artificial Neural Network

1. Introduction

The world population was estimated in 2010 at 6.9 billion people, of which about 5.7 billion live in developing countries [1]. Yet developing countries are home to 98% of the world's undernourished [2]. According to FIDA [3], around 925 million people are undernourished worldwide. About 200 million Africans (or 28% of the total population) suffer from chronic hunger [2]. Côte d'Ivoire, whose development relies on the agricultural sector, is no exception to the food insecurity situation affecting the African continent [2].

Faced with this situation, food crops considered as subsistence crops become important. These crops now play a key role in intercommunity and interregional trade and ensure the production of a wide range of agricultural products capable of improving household diets.

Among these food crops, cereals such as maize, rice and wheat have many agronomic and nutritional benefits.

With a world production of 2,765 million tonnes in 2019 [4], cereals occupy a central place in the agricultural system. Maize is the most widely produced cereal in the world at 1,148 million tonnes for an area of 197 million ha, with grain production slightly ahead of rice and wheat. It is the most widely practiced staple food crop in Africa with a production of 82 million tonnes [5]. Its cultivation occupies more than 40 million ha each year. It is practiced in a variety of production environments and is consumed by people with diverse food preferences and socio-economic backgrounds. It is estimated that over 300 million people depend on maize for their food and livelihoods [6]. In Côte d'Ivoire, maize occupies a prominent place both in the diet of the Ivorian populations and in animal nutrition. It is the most widely cultivated cereal after rice with an estimated national production of 1,100,000 tonnes [7] for a total area of 543,706 ha [5]. National consumption is estimated at 28.4 kg / inhabitant / year. In the human diet, the corn kernel is consumed in several forms (grilled cooked, in soup, etc.). It can be transformed to obtain a varied range of products such as flour and cornmeal. Also, it is used for making biodegradable plastics, biofuels and even alcohol [8].

Unfortunately, in recent years, the Ivorian territory has suffered the effects of climate change, one of the visible manifestations of which is the spatio-temporal variability of the rain. Added to this is the decline and variability in the level of soil fertility over short distances, thus affecting crop yields. Today the bitter observation of the decline in agricultural production is largely justified by these climatic and soil problems.

In the development and application of innovations and new techniques for a better management of cropping systems, it is therefore important to take into account the variability and dynamics of production conditions which imply that solutions must take into account the specificity of the site. This is why the present study proposes as a general objective to fill this deficit, by modeling the growth of maize for the control of the production which necessarily requires good growth in order to fight against poverty and food insecurity.

2. Material and Methods

2.1. Study Area

The study was carried out from May 26 to August 11, 2020 at the University Jean Lorougnon Guédé, located in the department of Daloa (Figure 1). The Department of Daloa is located in the Haut Sassandra region in the center-west of Côte d'Ivoire between 6° and 7° North latitude and 7° and 8° West longitude and at an altitude of 262 m by relative to sea level [9]. It has an area of 5,423 km^2. It is bounded by the departments of Vavoua to the north, Issia to the south, Zuénoula and Bouaflé to the east and Zoukoubgeu to the west. The department of Daloa includes the sub-prefectures of Gboguhé, Zaibo, Gonaté, Bédiala, Zoukougbeu, and Gadouan.

The climate of the department of Daloa is of the Guinean domain, humid with four (4) seasons. The main rainy season starts from April to mid-July, the short dry season from mid-July to mid-September, the short rainy season from mid-September to November and the long dry season from December to March [10].

The dry and wet seasons alternate with temperatures varying from 24°C to 28°C on average (Table 1). Annual rainfall fell from 1868.5 mm in 1968 to 1120.4 mm in 2005. The region is experiencing a drop in rainfall of around 40% [11]. The department is irrigated by the Sassandra river and its tributary the "Lobo" whoseramifications the Dé and the Gore flood all the localities [12]. Almost the entire basin is in a humid tropical zone with regressively evolving dense forest vegetation. Extensive and shifting cultivation practices and the uncontrolled exploitation of forest species have notably pushed back the limits of this forest [12]. The soils of the department of Daloa are of the ferralitic type of granitic origin, moderately to weakly denature. These ferralitic soils have good agricultural aptitudes and are suitable for all types of crops. They are generally very deep with a high organic matter value [13]. The pedological substrate belongs to the old Precambrian base composed of granites, migmatites. These soils, leached and deep (20 m) are due to abundant precipitation and rapid weathering of rocks

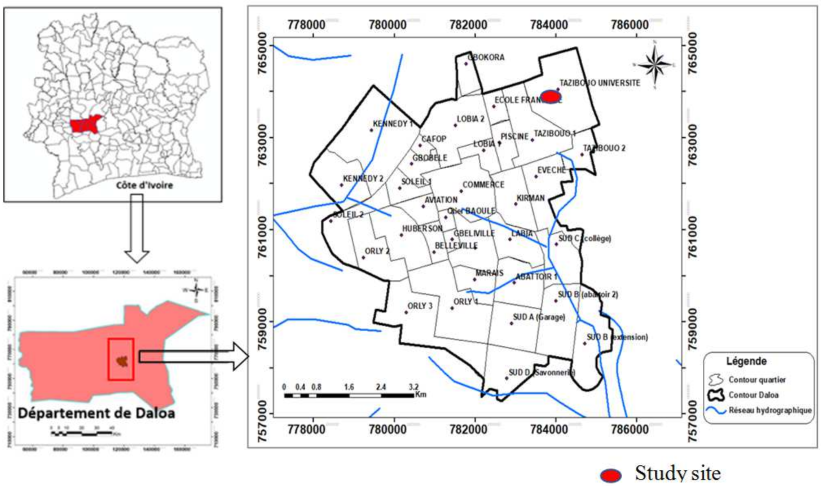

Figure 1. *Presentation of the study area.*

Table 1. *Evolution of the average climatic data of the city of Daloa during the experiment.*

Months	Medium temperature (°C)	Maximum temperature (°C)	Minimal temperature (°C)	Relative huminity (%)	Precipitations (mm)
May 2020	27.9	33.1	23.5	79.7	113.03
June 2020	26.4	30.6	22.9	84.6	107.18
July 2020	25.2	28.6	22.3	86.6	105.14
August 2020	25	28.8	21.8	83.8	109.74

Source: www.tutiempo.net

2.2. Plant Material

The plant material used in this study is composed of a CORN plant (Figure 2) from the variety EV8728 to short cycle, with horny seeds, semi-toothed yellow in color. The seeds of the maize variety were provided by the National Center for Agronomic Research (CNRA) of Korhogo (Côte d'Ivoire).

Figure 2. *Maize plant.*

2.3. Technical and Experimental Methods

2.3.1. Preparation of the Ground

The preparation of the land began with the clearing of the plot. It was followed by shallow manual plowing. This plowing consisted of moving and turning the soil with the help of dabas and hoes. After these two activities it was a question of proceeding to the realization of our various ridges.

2.3.2. Maintenance of the Plot

Maintenance of the plot consisted of carrying out weeding on the 15th and 21st day and then between the 30th day and 45th day after sowing. The plants were stripped 15 days after emergence. Then, watering twice a day (from the 1st to the 3rd week) was done.

2.3.3. Experimental Apparatus

The test was arranged as a three-repeat Fischer block. Each block consists of two ridges. Each log has 20 pockets 4 cm deep and spaced 40 cm apart on the line, for a density of 21 428 plants / ha. The ridges are one meter apart and are 8 m long each. The semi was carried out due to 3 seeds per pocket and on the same day.

2.3.4. Maize Growth Parameters

Growth measurements are taken in centimeters and noted on a card. Observations focused on the vegetative apparatus, including the foot for height and diameter and the last functional leaf for number of leaves, length and width. They started after two weeks of cultivation and ended at flowering. Measurements of growth and development parameters were weekly. The observations were made on a staff of 10 feet per ridge chosen among the 120 of the plot taken according to their vigor.

(i) Leaf Dimensions

Leaf growth was assessed weekly by measuring the length (Lg) of the last functional leaf, from the base of the blade to the end of the blade that is to say at the level of the precursor filament. The width (lg) of the leaf was evaluated by considering the largest dimension of the middle part of the organ. The values were expressed in centimeters.

(ii) Plant Dimensions

Height and diameter were the parameters measured to track plant growth. Plant height (Ph) was measured from the crown to the top of the plant. The diameter was measured at the base of the plant more precisely at the crown.

(iii) Development parameters

The general development of the maize was assessed by the number of leaves emitted (Nl) during the duration of the experiment. It was measured together with that of the growth parameters.

2.3.5. Growth Modeling Approach by the Empirical Model

In this study, the modeling of maize growth was carried out by an empirical model using as a tool artificial neural networks according to the Kouamé [14].

(i) Modeling of Maize Growth by Artificial Neural Network

The modeling of the growth of corn was carried out using an artificial neural network through a program developed in the Matlab R2010b software (Math Works Inc., Massachusetts USA). This program made it possible to set up an empirical model which was developed in several stages.

A. Determination of input parameters and output parameters of the artificial neural network

The growth parameters (explanatory parameters) followed was used to explain and predict the maize growth. They respectively represented the input parameters at time t and the output parameters at time t+1 of the artificial neural network (Table 2). To facilitate the mathematical expression of the model, symbols have been assigned to the various parameters.

B. Construction and preparation of the database

The database was made up of measurements taken in the field during the growth of corn plants. Then these implemented in the artificial neural network module of the Matlab R2010b software (Math Works Inc., Massachusetts USA), underwent a standardization step in the range [-1; +1] according to the equation:

$$x_{ni} = \frac{2(x_i - x_{\min})}{(x_{\max} - x_{\min})} - 1 \quad (1)$$

With

x_{ni} = normalized data ranging between -1 and +1, xi = initial data,

x_{min} and x_{max} =minimum and maximum values of all data.

This normalization reduces dispersion errors by accelerating the convergence of the network during training, and increases its generalization efficiency. This standardized database was subsequently split into three subsets, at random, for the determination of the network connection weights. This sharing avoids the two pitfalls that the artificial neural network can encounter, namely, the existence of local minima and over fitting. A first group of data (50%) served as a learning base. In the second group, a quarter of data was used for validation. The second subgroup of data (25% remaining) made it possible to test the validity of the model which was retained.

Table 2. *Parameters of inputs at time t and outputs at time t + 1 of the artificial neural network.*

Parameters	Number of leaves	Leaves length	Leaves width	Plant height	Diameter at collar
Entrance	Nl (t)	Lg (t)	wi (t)	Ph (t)	Diam (t)
Exit	Nl(t+1)	Lg (t+1)	Wi(t+1)	Ph (t+1)	Diam (t+1)

with: Nl= Number of leaves; Ph = plants height; Diam = Diameter at collar; Lg = Leaves length; wi = Leaves width

C. Development of the structure of the artificial neural network

In the development of the artificial neural network, the most difficult part is the determination of its structure which is done by the choice of the architecture, the number of hidden layers, the number of neurons on the hidden layers and the functions transfer between neurons.

(a) Architecture

In this study, the basic architecture adopted was the multilayer perceptron (MLP) with three types of layers (input, hidden and output). It includes five input neurons corresponding to the five input variables at time t and five output neurons corresponding to the five output variables at time t + 1 (Figure 3). This multi-layered perceptron was chosen in this study because it appears to be the easiest to use and capable of modeling any continuous function [15]. Once the architecture of the artificial neural network has been defined, all that remains is to determine the number of hidden layers, the number of neurons in the hidden layer and the activation function.

(b) Number of hidden layers and hidden neurons

The number of hidden layers can vary between one and two. However, note that a multilayer perceptron with a single hidden layer with a sufficient number of neurons can approximate any function with the desired precision [16]. The number of hidden neurons k was arbitrarily varied from 1 to 15 in the hidden layer until an optimal architecture was achieved.

(c) Activation functions.

A tangential-type sigmoid transfer function has been adopted as the activation function of neurons in hidden layers. This is a nonlinear function allowing the expression of nonlinear phenomena such as the growth of corn. Indeed, without non-linearity, artificial neural networks are no more powerful than a generalized linear model [17]. Thus, it is therefore important to choose the activation function well to obtain a well-built model. A linear function was used to directly assign neurons to the output layer.

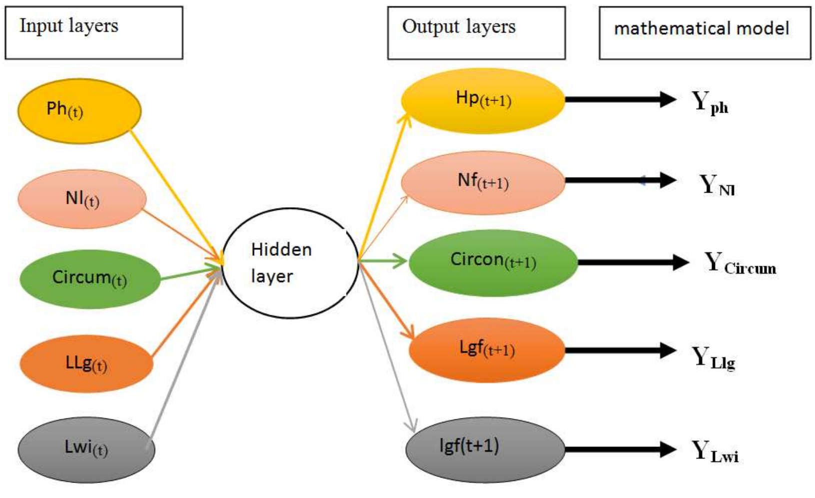

Figure 3. *Curly neural network with 5 input layers, one hidden layer and 5 output layers.*

(ii) Learning and Validation of the Neural Model

The training in this work used the back propagation algorithm. The algorithm initially propagates the input forward until it obtains an output through the network. The second step was to compare the calculated output to the known actual output. The mistake was back-propagated back to the entry layer. Thus, the weights called "weight" are then modified so that on the next iteration, the error made between the calculated and measured outputs is minimized. This process was repeated on all examples until we got an acceptable output error. In our study, to achieve good results, we repeated the calculations 1500 times for each k € [1; 15], number of hidden neurons.

The validation phase took place simultaneously with the learning phase. Thus, each time the weights have been determined in the learning phase, the absolute error

Δy (calculated value Y_{pred}– experimental value y_{exp}) was measured throughout the validation.

However, the validation of the neural model was performed by the Correlation Coefficient (R) between the predicted values and the experimental values, by the Medium Quadratic Error (MQE) for different architectural behaviors and the coefficient of determination (R^2).

A. Correlation Coefficient (R)

The correlation coefficient (R) is commonly used to evaluate the performance of mathematical models. It is obtained by making the linear regression between the experimental values and the values predicted by the network. When the absolute value of the correlation coefficient (R) between the experimental values and those predicted by the network tends towards zero (0), the degree of connection is weak. On the other hand, when it is close to 1, the reciprocal bond is strong [18]. Its formulation is developed as follows:

$$R = \frac{\sum_{i=1}^{N}\left(y_e - \overline{y_e}\right)\left(y_c - \overline{y_c}\right)}{\sqrt{\sum_{i=1}^{N}\left(y_e - \overline{y_e}\right)^2}\sqrt{\sum_{i=1}^{N}\left(y_c - \overline{y_c}\right)^2}} \quad (2)$$

With:

y_e and y_c which are respectively the experimental values and the values calculated by the network for the i=1,…, N, $\overline{y_e}$ and $\overline{y_c}$ which are the respective means of the experimental values and the values calculated by the network, N which corresponds to the number of variables.

B. Mean Square Error (MSE)

The mean square error (MSE) is generally used to measure the performance of the learning stage during neural model development. The expression of the mean squared error (MSE) is presented as follows [19].

$$EQM = \frac{1}{N}\sum_{i=1}^{N}\left(y_e - y_c\right)^2 \quad (3)$$

With:

y_e and y_c which are respectively the experimental values and the calculated by the network for the i = 1,…,N

N = number of input variables.

C. Coefficient of determination (R^2)

The values predicted by the model and those experimental were simulated with the Matlab R2010b software (Math Works Inc., Massachusetts USA). The quality performance of the forecast was determined by the coefficient of determination (R^2). This coefficient is used to measure the goodness of fit of the estimates of the regression equation. It is used to get an overall idea of the fit of the models developed in this study.

When R^2 is close to 1 in the case of a simple regression, the fit between experimental and predicted values is better [20]. The expression of the coefficient of determination (R^2) is given by the following equation:

$$R^2 = \frac{\sum_{i=1}^{N}\left(y_{pr?d} - \overline{y_e}\right)^2}{\sum_{i=1}^{N}\left(y_e - \overline{y_e}\right)^2} \quad (4)$$

With:

y_e and y_{pred} being respectively experimental values and calculated for i=1,…,N

$\overline{y_e}$ being the average of measured or experimental values

3. Results

3.1. Neural Network Architecture

The search for the conditions for a good forecast of maize growth was carried out on the basis of the growth parameters monitored previously. Thus, the modeling of maize growth began with the determination of the neuronal architecture that allows better adjustment of the experimental measurements. The number of "k" neurons in the hidden layer that optimizes the artificial neural network has been determined. This amounts to determining the hidden neurons allowing a good correlation coefficient (R) between the predicted values and the experimental values. Mean Squared Errors (MSEs) were also used to determine the optimal network.

Table 3 shows the values of the correlation coefficients (R) during the learning and validation phases in the plot. Analysis of the results of this table shows that the highest correlation coefficient (R) in the learning phase for the number of leaves is that of the hidden neurons 9; 12; 13; 14 and 15 then 8; 4; 7; 2; 3 for the validation phase. At the leaf size level, the correlation coefficients (R) are higher during the learning phases for hidden neurons 11; 13; 15; 8; 12; 9 and 14 then 3; 9; 4; 5; 11; and 7 for the validation phase. Regarding the height and diameter of the plant, these are the hidden neurons 10; 12; 13; 14 and 15 which have the highest correlation coefficients (R) in the learning phase while for the validation phase, these are the hidden neurons 3; 4; 5; 7; 15; 8; 9 and 12. It emerges from the above that the most efficient hidden neurons with regard to the correlation coefficients (R) are neurons 2; 3; 4; 7 and 15, that is, five neural architectures. The choice of the best predictive neural model among these five neural architectures was once again determined by the Mean Squared Error (MSE) (Figure 4). Analysis of this figure shows two main phases. A first phase during which, the Mean Squared Errors (MSE) decrease exponentially. From this phase, the (MQE) evolve in a stable manner. However, the stability of the evolution of MSEs is earlier for the hidden neuron 3. It emerges from these combined analyzes (correlation coefficient (R), Mean Squared Error), that the neuronal architecture which is the best compromise (taking into account the weak MQE, the R closer to the value 1) is that of the neuron hidden 3. Which gives a 5-3-5 topology. This topology has five neurons in the input layer, three neurons in the hidden layer, and five neurons in the output layer. The 5-3-5 neural architecture of the plot has yielded several mathematical models to predict corn growth.

$$Y_{Nf} = 0.59\ Y'_1 + 1.17\ Y'_2 - 0.31\ Y'_3 + 0.06$$

$$Y_{Lf} = 0.72\ Y'_1 + 0.97\ Y'_2 - 0.46\ Y'_3 + 0.19$$

$$Y_{lf} = 0.57\ Y'_1 + 0.53\ Y'_2 - 0.63\ Y'_3 + 0.11$$

$$Y_{Ht} = 0.46\ Y'_1 + 1.56\ Y'_2 - 0.08\ Y'_3 - 0.17$$

$$Y_{D} = 1.28\ Y_1' + 1.32\ Y'_2 - 0.19\ Y_3' + 0.58$$

With:

$$Y'_1 = \text{Tanh}\ [0.13\ Nf_{(t+1)} + 0.33\ Lf_{(t+1)} - 0.02\ lf_{(t+1)} - 1.31\ Ht_{(t+1)} + 0.86\ D_{(t+1)} - 1.18]$$

$$Y'_2 = \text{Tanh}\ [0.20\ Nf_{(t+1)} - 0.23\ Lf_{(t+1)} - 0.13\ lf_{(t+1)} + 0.95\ Ht_{(t+1)} - 0.17\ D_{(t+1)} + 0.37]$$

$$Y'_3 = \text{Tanh}\ [-0.22\ Nf_{(t+1)} - 1.27\ Lf_{(t+1)} - 1.99\ lf_{(t+1)} - 0.02\ Ht_{(t+1)} + 0.82\ D_{(t+1)} - 1.76]$$

Table 3. *Correlation coefficients (R) during the learning and validation phases.*

Hidden layer neurons	Correlation coefficients (Learning phase)				
	Nl	**Ll**	**Lw**	**Hg**	**Diam**
1	0.9783	0.9662	0.9163	0.9442	0.9777
2	0.9804	0.9747	0.9619	0.9772	0.9759
3	0.9804	0.9753	0.9627	0.9781	0.9825
4	0.9814	0.9760	0.9630	0.9800	0.9827
5	0.9825	0.9761	0.9636	0.9812	0.9844
6	0.9826	0.9768	0.9637	0.9808	0.9861
7	0.9823	0.9773	0.9687	0.9796	0.9840
8	0.9834	0.9775	0.9709	0.9814	0.9847
9	0.9844	0.9793	0.9701	0.9816	0.9851
10	0.9840	0.9801	0.9651	0.9822	0.9848
11	0.9829	0.9824	0.9708	0.9809	0.9862
12	0.9860	0.9801	0.9683	0.9853	0.9844
13	0.9862	0.9816	0.9723	0.9830	0.9855
14	0.9852	0.9821	0.9677	0.9823	0.9858
15	0.9862	0.9825	0.9705	0.9824	0.9874
	Correlation coefficients (validation phase)				
1	0.9786	0.9677	0.7399	0.9449	0.9717
2	0.9822	0.9728	0.7428	0.9715	0.9694
3	0.9830	0.9725	0.7440	0.9715	0.9721
4	0.9811	0.9768	0.7483	0.9705	0.9710
5	0.9764	0.9745	0.7467	0.9693	0.9674
6	0.9786	0.9716	0.7458	0.9647	0.9717
7	0.9821	0.9715	0.7491	0.9684	0.9740
8	0.9798	0.9711	0.7385	0.9635	0.9750
9	0.9787	0.9724	0.7450	0.9609	0.9742
10	0.9760	0.9720	0.7437	0.9633	0.9685
11	0.9764	0.9653	0.7490	0.9645	0.9707
12	0.9781	0.9709	0.7442	0.9634	0.9706
13	0.9758	0.9700	0.7396	0.9595	0.9673
14	0.9750	0.9703	0.7440	0.9636	0.9691
15	0.9761	0.9696	0.7479	0.9632	0.9721

Hg: Height; Nl: Number of leaves; Diam: Diameter; Ll: Leaf length; lw: leaf width.

*The values in bold correspond to the correlation coefficients (R) chosen

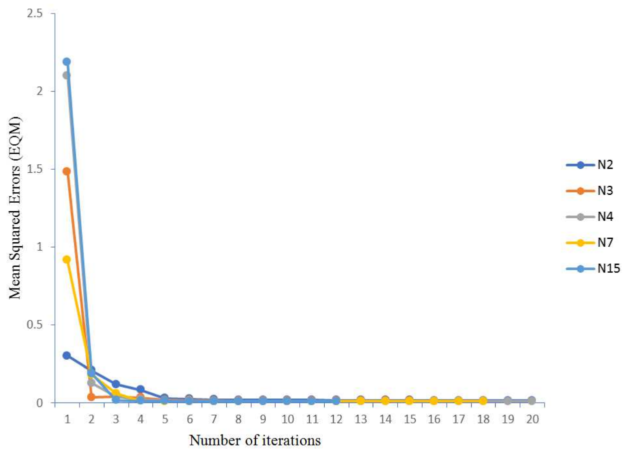

Figure 4. *Evolution of the Mean Squared Errors of the different neuronal.*

3.2. Validation of the Optimized Neural Model

The validation of neural models of topology 5-3-5 was carried out by the coefficients of determination (R2) between the values predicted by the network and the experimental values of the remaining measurements from the database.

The neural topology model 5-3-5 predicting and simulating the number of leaves (Nl), Leaves length Ll), Leaves width (lw), height (Hg), diameter at collar, is compared with the experimental values in Figures 5; 6; 7; 8; 9. The changes observed in the number of leaves, the length and width of the leaves and the height and diameter of the plants observed experimentally are compared with those predicted by the model. The coefficients of determination (R2) between the values predicted by the network and those coming from experiments vary between 0.9872 and 0.9995. These are all values greater than 0.98 and therefore very close to 1.

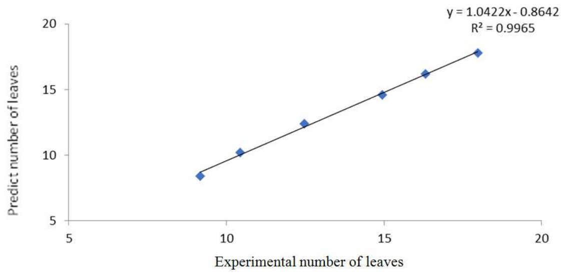

Figure 5. *Regression curve between the values predicted by the 5-3-5 network and the experimental values of the number of leaves.*

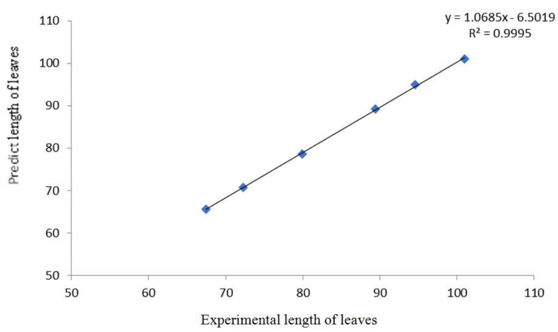

Figure 6. *Regression curve between the predicted by the 5-3-5 network and the experimental values of the length of leaves.*

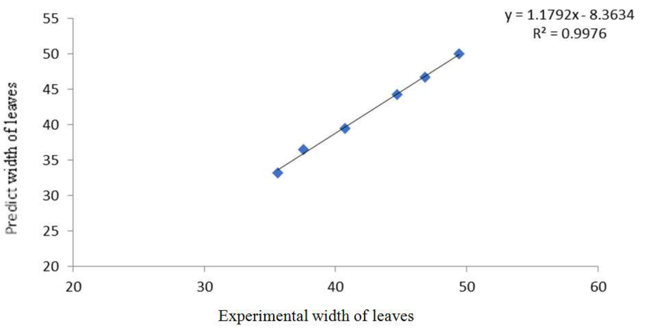

Figure 7. *Regression curve between the predicted by the 5-3-5 network and the experimental values of the width of leaves.*

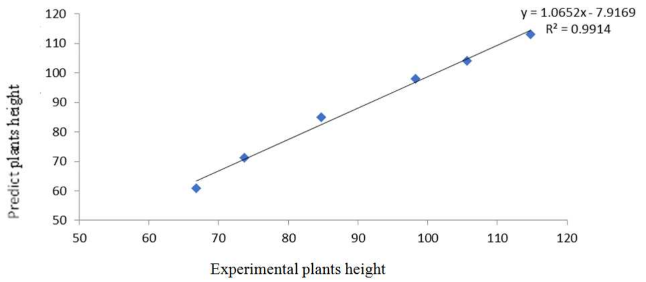

Figure 8. *Regression curve between the predicted by the 5-3-5 network and the experimental values of the plants height.*

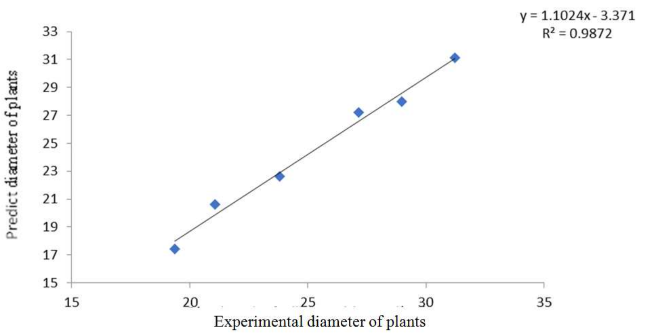

Figure 9. *Regression curve between the values predicted by the 5-3-5 network and the experimental values of the diameter of plants.*

4. Discussion

The performance criteria presented in the second part of this study were used to determine the quality of the prediction of maize growth by the empirical model. The empirical model used artificial neural networks as an algebraic tool or function to model the growth of corn from the number of leaves, leaf length and width, height and diameter.

The first phase of the modeling by artificial neural networks of maize growth began with the implementation of the neural architecture allowing to better adjust the experimental values to the neural model. The network started with a small architecture, and then it grew to a size that gives a good forecasting model [21]. This methodology made it possible to vary the number of neurons k in the hidden layer arbitrarily from 1 to 15 [22].

This contributed to choosing the best performing artificial neural network to better approximate the growth of corn across the five growth parameters.

The validation of the models from the 5-3-5 topology was done by comparing the predicted values with the experimental values [23]. The regression line obtained from this comparison is characterized by its coefficient of determination (R^2). The coefficients of determination (R^2) obtained are greater than 0.98 (therefore very close to 1). The 5-3-5 neural architecture (that is to say five input neurons, three neurons in the hidden layer and five output neurons) was therefore chosen as the best topology. The topology 5-3-5 neural network therefore makes it possible to predict the growth of corn at a value greater than 98%. These results corroborate those of Kouamé et al [24, 25]. These authors obtained coefficients of determination (R^2) close to 1, on the modeling of the growth of plantain. This attests to the ability of artificial neural networks, in general, to make approximations in the field of modeling dynamic phenomena such as corn growth.

5. Conclusion

The modeling was carried out from the empirical model using the artificial neuron network from the experimental measurements in the field. It was carried out on the basis of five corn growth parameters. These are the number of leaves, the length and width of the leaves, the height and diameter at the neck. The experimental measurements were able to reveal a complexity of corn growth which was capitalized by mathematical models.

Models using the artificial neural network as a tool have successfully predicted the growth of maize from operating variables. These models gave a close match between the values of the experimental operating variables and those calculated by the network. The coefficients of determination R^2 are greater than 0.98 and therefore close to 1.

Ultimately, it will be remembered that artificial neural networks are efficient models for simulating and predicting corn growth.

References

[1] UNFPA, (2010). State of the world population, New York, 99p.

[2] Kinimo, R. Y. (2013). Determinants of household undernourishment in Côte d'Ivoire: the case of the central and central-eastern regions. *European Scientific Journal 9 (14)*: 22p.

[3] FIDA, (2011). Global Food and Nutrition Security Perspectives. 2015 International Hunger Reduction Goals: Uneven Progress, Quarterly Bulletin, 2p.

[4] FAO, (2019). FAO Maize Supply and Demand Bulletin http://www.fao.org/faostat/fr/#data/QC/visualize. Site visited le 15/12/2020.

[5] FAOSTAT, (2019). Agricultural production, crop primary database. Food and agricultural organization of the United Nations, Rome. http://faostat.fao.org/faostat/.Consulté le 20/12/2020

[6] FAOSTAT, (2015). Agricultural production, crop primary database. Food and agricultural organization of the United Nations, Rome. http://faostat.fao.org/faostat/.Consulté le 20/12/2020

[7] FAO, (2018). Food and agricultural organization of the United Nations, http://www.fao.org/faostat/fr/#data/QC/visualize. Site visited le 15/12/2020.

[8] Hoopen, M. E. T. and Maïga, A. (2012). Maize production and processing, Collection Proagro, Cameroun, 29 p.

[9] Yao, A. B., Goula, B. T. A., Kouadio, Z. A., Kouakou, K. E., Kané, A. and Sambou, S. (2012). Analysis of climatic variability and quantification of water resources in humid tropical zone 56: case of the Lobo watershed in the center-west of the Côte d'Ivoire. Review *Ivoirienne des Sciences et Technologiques,* 19: 136-157.

[10] N'Guessan, A. H., N'Guessan, K. F., Kouassi, K. P., Kouamé, N. N. and N'Guessan, P. W. (2014). Population dynamics of the cocoa stem borer, *Eulophonotus myrmeleon*. Felder (Lepidoptera: Cossidae) in the Haut-Sassandra region of Côte d'Ivoire, *Journal of Applied Biosciences* 83: 7606-7614.

[11] Ligban, R., Gone, L. D., Kamagate, B., Saley, M. B. and Biemi, J. (2009). Hydrogeochemical process and origin of natural sources in the Daloa square degree, *Int. J. Biol. Chem. Sci.* 3(1): 38-47.

[12] Sangaré, A., Koffi, E., Akamou, F. and Fall, C. A. (2009). State of plant genetic resources for food and agriculture. Second report. 65p

[13] Soro, D., Ayolié, K., Zro, B. F. G., Yao, F. Y., Konan-Kan, K. H., Sidiky, B., Téhua, P. and Yatty, K. J. (2015). Impact of organic fertilization on maize (zea mays l.) production in a ferralitic soil of centre – west Côte d'Ivoire, *Journal of Experimental Biology and Agricultural Sciences,* 3 (6): 556-565.

[14] Kouamé, N. (2014): Modeling the growth of plantain from artificial neuron networks, case of Yamoussoukro and Azaguié (Côte d'Ivoire), Doctorate Thesis, Félix Houphouet-Boigny University, (Côte d'Ivoire), 252 p.

[15] Hornik, K., Stinchcombe, M. and White, H. (1989). Multilayer feed-forward networks are universal approximators. *Neur. Net. comp*, 2: 359-366.

[16] Hornik, K. (1991). Approximation capabilities of multilayer feedforward networks. *Neur. Net. comp*, 4: 251-257.

[17] Koffi, Y. B. (2007). Study of the calibration, validation and performance of neural networks from hydro-climatic data from the Bandama Blanc watershed (Côte d'Ivoire). Doctorate Thesis. University of Cocody, Abidjan, Côte d'Ivoire. 240 p.

[18] Thompson, M., Walton, S. J. and Wood, S. J. (1979). Statistical appraisal of interference effects in determination of trace elements. *Ana. Sci. Chem*, 104: 299-312.

[19] Hagan, M. T., Demuth, H. B. and Beale, M. H. (1996). Neural network design, *PWS, Boston, MA*, 259 p.

[20] Feinberg, M. (1996). Validation of analytical methods; a chemometric approach to quality assurance in the laboratory, *Ed. Mas,* Paris, France. P 56-57.

[21] LeCun, Y., Dznker, J. S. A. and Solla, S. A. (1990). Optimal brain damage: proceeding of the neural information processing systems. *Sci. comp. contr*, 2: 598-605.

[22] Dreyfus, G., Martinez, J. M., Samuelides, M., Gordon, M. B., Badran, F., Thiria, S. and Herault, L. (2002). *Artificial Neural Networks*. New York, USA: *Gr. Eyrol*, 374 p.

[23] Benaissa, W. (2006). Development of a methodology for the safe operation of an intensified continuous reactor, PhD thesis, *I. N. P. Toulouse* 203 p.

[24] Kouamé, N., Assidjo, N. E., Dick, A. E. and Anno, A. P. (2013). Plantain tree growth (*Musa sp*., AAB cultivar horn 1) modeling using the artificial neural networks method. *European Scientific Journal*, 33 (9): 272-285.

[25] Kouamé, N., Assidjo, N. E. and Dick, A. E. (2017). Illustration of the growth of plantain (Musa sp., AAB, cultivar Corne 1) in the localities of Yamoussoukro and Azaguié (Cote d'Ivoire) using mathematical models. *Agronomie Africaine,* 29 (2): 135–147.